ESTIMATION OF ENERGY USAGE IN ELECTRIC AND DIESEL VANS FOR LOGISTICS APPLICATIONS USING GAUSSIAN PROCESSES

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Background

A rapid rise in online shopping has recently led to a substantial increase in the quantity of goods deliveries. For example, in the United Kingdom, van traffic grew by 104% between 1990 and 2019. This phenomenon was further accelerated by the Covid-19 pandemic with a significant increase in home deliveries during lockdown. This increase in van traffic has inevitably contributed to a growth in greenhouse gas (GHG) emissions, which already induced a 19% rise in emissions attributed to heavy goods vehicles between 2012 and 2018, and an equivalent rise of 14% for vans.

In order to meet their net-zero targets, one of the key pathways that worldwide governments need to follow is a reduction of GHG emissions from road transportation. In conventional diesel vans the energy savings can be immediately achieved, for example, by solving the Green Vehicle Routing Problem (GVRP) which chooses the order of the visited locations so that the route is driven in an energy efficient manner. This solution is also relevant to electric vans despite not producing tailpipe emissions due to constraints on their range because of limited battery capacities.

In order to solve the GVRP, an accurate estimate of the vans energy consumption is required before commencing the journey. At the optimisation stage, only the most elementary information about the trip is available, for example historical travel times along road segments and associated mean speed. Knowledge about the frequency and rate of speed fluctuations, a significant factor contributing to energy consumption, is unknown. Nonetheless, if these are ignored, energy usage can be underestimated by up to 80% for some driving styles. It is demonstrated that certain degrees of information about speed fluctuations can be deduced from the value of mean speed, which in turn leads to a more accurate estimate of energy consumption.

Research Aim

The aim of this research was three-fold: i) to formulate a new model where statistical correction based on Gaussian Processes is applied to a physics-based energy consumption model to approximate energy usage due to speed fluctuations; ii) train energy consumption models for electric and diesel vans using historical speed profiles collected in the United States; and iii) to evaluate accuracy using real-life data sets collected in the Solent region of the UK.

Methodology

The methodology to estimate energy consumption for electric and diesel vans consists of two parts: i) Calculation of energy consumption using an instantaneous physics-based model. At this stage, it is assumed that the vehicle travels at a constant historical mean speed with zero acceleration; ii) Statistical correction to the energy estimated in the form of multiplicative factors that are a function of historical mean speed.

Instantaneous energy consumption models
The CPEM and CMEM are chosen for electric and diesel vans respectively. Both are based on mechanical power calculation which in our case considers aerodynamic drag, surface friction and engine or motor force. Subsequently, the mechanical power is converted to energy and fuel consumption following models of engine, motor and powertrain efficiencies. Primary differences between CPEM and CMEM is that the first model includes regenerative breaking whilst the second introduces an idle fuel consumption term which does not depend on time varying quantities.

Statistical correction using Gaussian Processes
Two approaches to apply statistical corrections are introduced here: i) Statistical adjustment applied directly to total energy and fuel consumption. ii) Two distinct statistical corrections applied to mass-dependent and mass-independent terms. The latter formulation is particularly relevant in logistics applications where the payload mass changes between the trips. The form of multiplicative coefficients is calculated using Gaussian Processes Regression (GPR), which is a non-parametric, Bayesian approach to regression problems.

Training model on historical data
The historical data used for this analysis was collated by the National Renewable Energy Laboratory and contains measurements obtained in several different regions of the US, such as Greater Fairbanks, Kansas and Detroit as part of Household Travel Survey. The number of driving cycles used for the training the model is 20,426 and their statistical properties are presented in Table 1. In this study, the input consists of mean speeds associated with trips included in the Household Travel Survey, whilst the output is a ratio between physics-based models applied to corresponding speed profiles on an instantaneous basis and to the constant speed profile. The GPR models for diesel and electric vans are shown in Figures 1 and 2 respectively. All diesel van models in Figure 1 show clear maximum values at intermediate speeds which implies that approximation using constant speed will result in the largest error for urban environments. The form of the GPR prediction is substantially different for electric vans where the highest ratio is visible for slow trips. The reduced values of the ratios at intermediate speeds are primarily caused by regenerative breaking.

TABLE 1. Statistical properties of historical driving cycles

	Maximum	Minimum	Average	Median	Standard Deviation
Mean Speed [m/s]	33.7	0.4	12.3	12.0	5.1
Duration [min]	158.9	1.0	6.0	3.6	7.1
Distance [km]	321.4	0.1	5.3	2,4	8.7

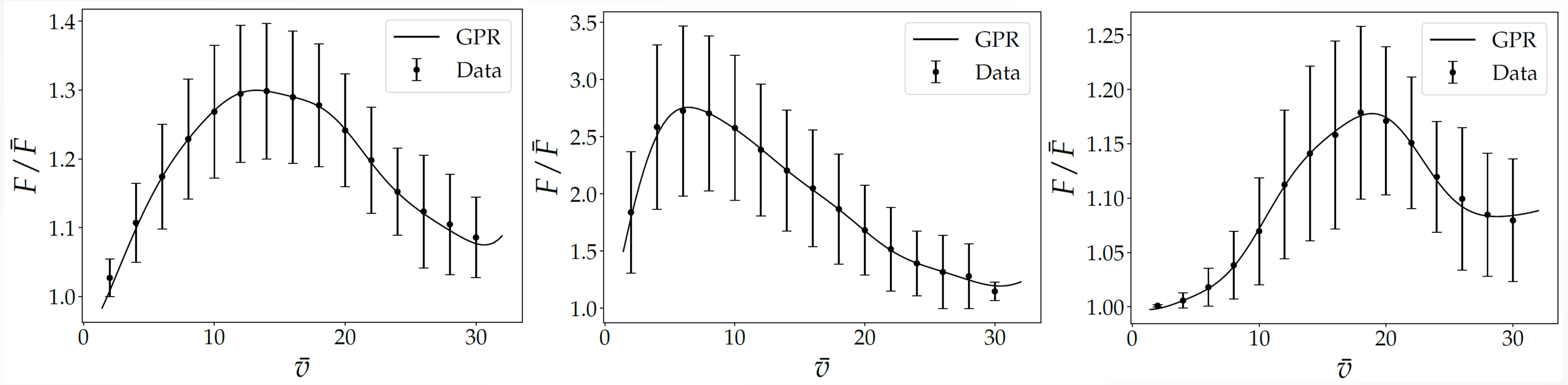

FIGURE 1. The form of statistical coefficients for a diesel van when applied to the total energy consumption (left), to the mass-dependent term (middle) or to mass independent term (right).

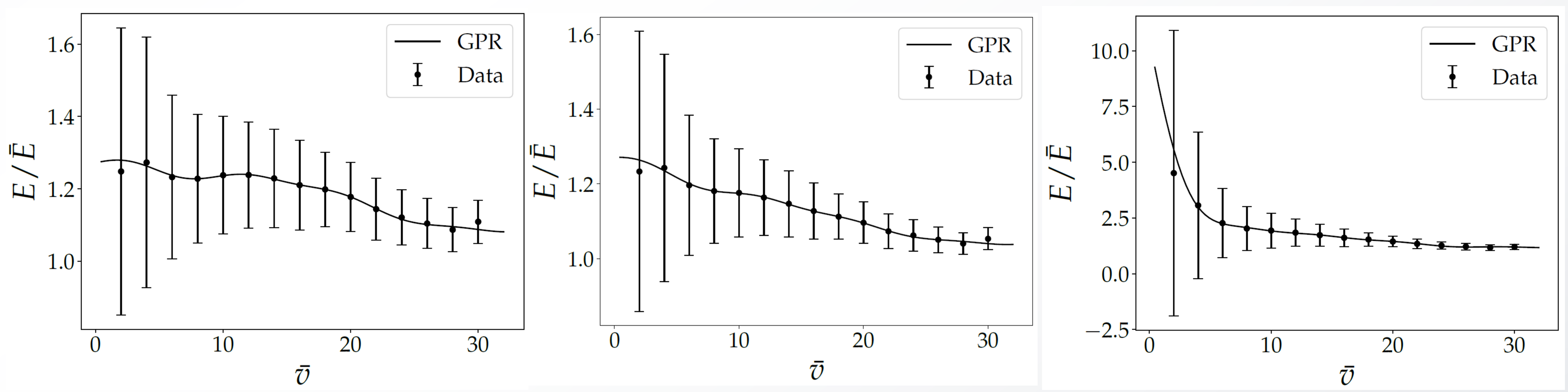

FIGURE 2. The form of statistical coefficients for an electric van when applied to the total energy consumption (left), to the mass-dependent term (middle) or to mass independent term (right).

Experimental evaluation

The proposed model was evaluated using data collected while imitating usage of electric and diesel vans in logistics applications in the Solent region of the UK. The first application involves visiting surgeries that produce patient diagnostics which have to be delivered to Southampton General Hospital. For a diesel van, the chosen route consisted of 33 addresses and is shown in Figure 3-4. A similar approach was used to collect data for evaluation of electric van models. In this case, the chosen route consists of 12 addresses and is shown in Figure 5. The number of visited addresses was smaller than for the diesel van because of driving range limitations. Consequently, the dataset was supplemented using the second logistics application consisting of fruit delivery around an urban area of Southampton and consisted of 21 postcodes.

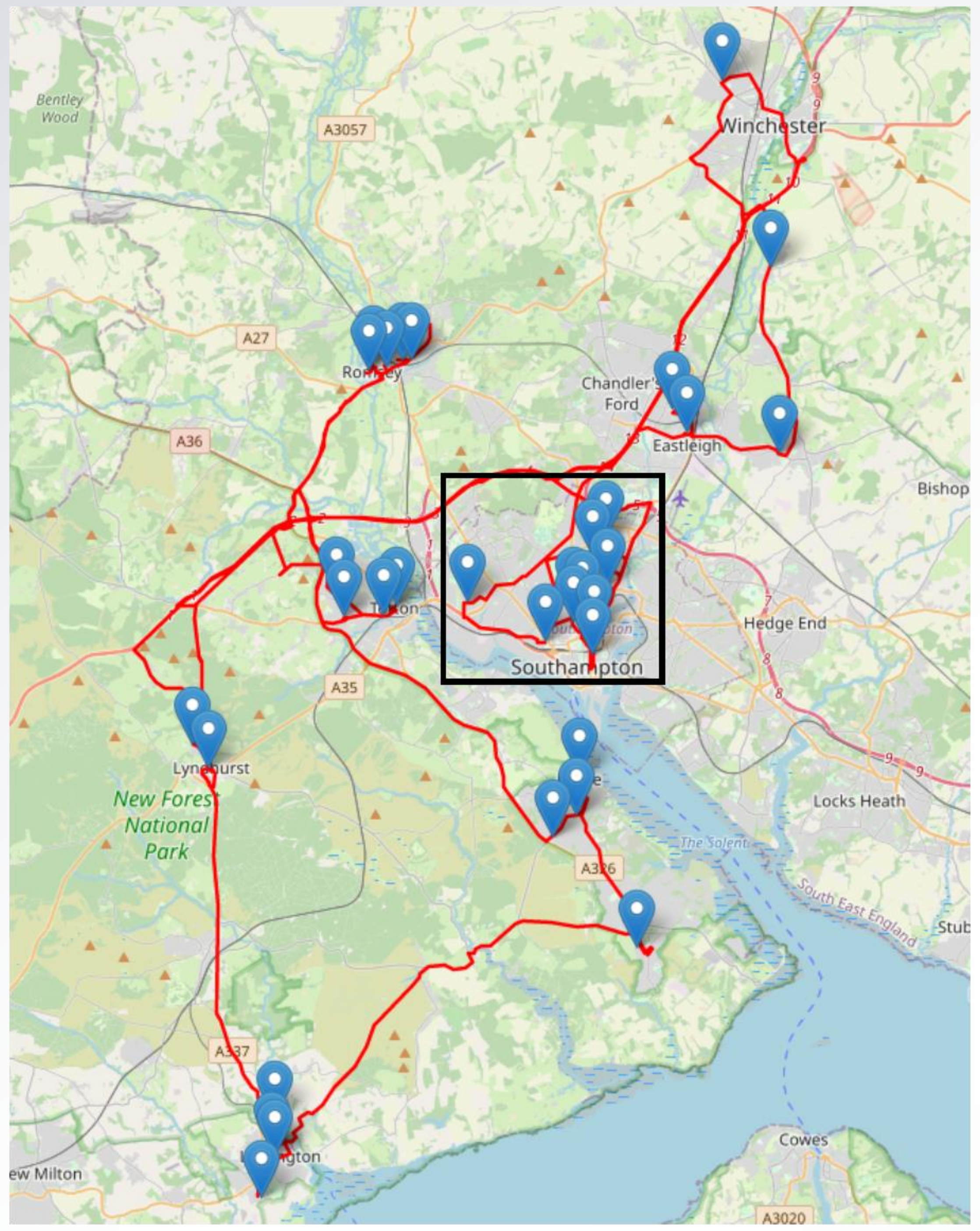

FIGURE 3. The route of the diesel van.

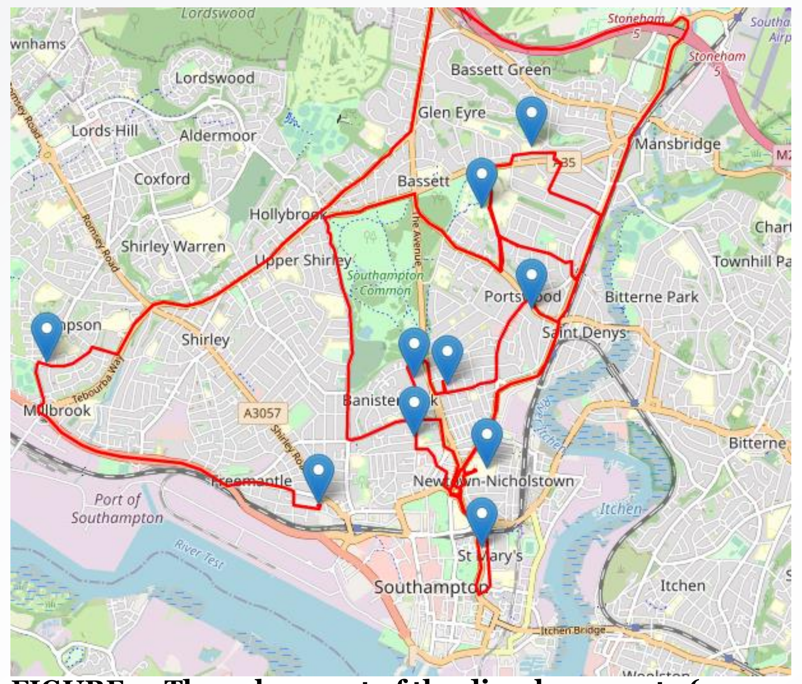

FIGURE 4. The urban part of the diesel van route (see black square in Figure 3)

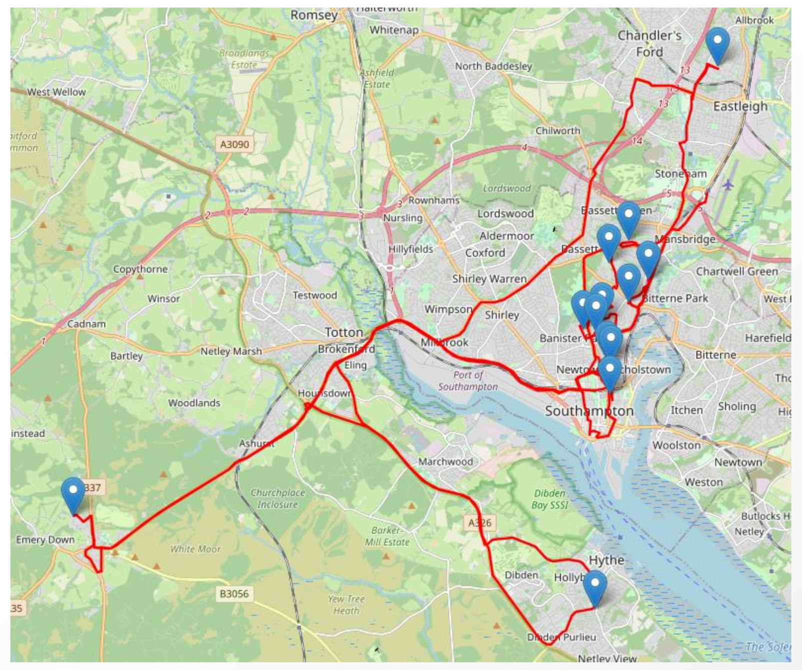

FIGURE 5. Route of the electric van

Results

The evaluation is performed on a trip basis, where a single trip commences and ends at one of the surgeries or delivery addresses. Two metrics are defined to evaluate accuracy of the models i) error in energy consumption over the whole trip, ϵ_E (which prioritises long trips) and ii) and error in average power consumption, ϵ_P, which considers every trip equally. Table 2, shows the values of ϵ_E and ϵ_P for the following methodologies 1) CMEM and CPEM applied to speed profiles associated with each trip on an instantaneous basis 2) CMEM and CPEM with statistical correction applied directly to total energy and fuel consumption (respectively referred to as 'CMEM-1STAT' and 'CPEM-1STAT') 3) CMEM and CPEM with statistical corrections applied to mass-dependant and mass independent terms of energy and fuel consumption (respectively referred to as 'CMEM-2STAT' and 'CPEM-2STAT'). Those models are compared again CMEM and CPEM applied to trips which assume constant speed (respectively referred to as 'CMEM-CONST' and 'CPEM-CONST'). Furthermore, the models corresponding to diesel van are compared against the COPERT model that uses average travel speed as an input and is used by European Union countries to report their national emissions.

TABLE 2. The error values for trips between surgeries.

Electric Van					
	COPERT	CPEM	CPEM-CONST	CPEM-1Stat	CPEM-2STAT
ϵ_E	N/A	0.388	0.549	0.445	0.445
ϵ_E [kW]	N/A	1.1211 (41.4%)	1.490 (40.7%)	1.267 (39.2%)	1.267 (39.2%)
Diesel Van					
	COPERT	CPEM	CPEM-CONST	CPEM-1Stat	CPEM-2STAT
ϵ_P	0.738	0.177	0.336	0.165	0.161
ϵ_P [ml/s]	0.679 (51.8%)	0.271 (21.8%)	0.392 (27.9%)	0.205 (14.9%)	0.200 (14.6%)

Discussion and Conclusions

Table 2 shows that CPEM models with statistical correction outperform CPEM-CONST where constant speed is used. For electric vans both CPEM-1STAT and CPEM-2STAT result in nearly identical performance. This is the result of the mass-dependent term heavily dominating power consumption of an electric van. Furthermore, it is noted that even for instantaneous CPEM, where a velocity profile sampled every 6s is used, significant error persists, which implies that this temporal resolution does not take into account high frequency variations which have a significant impact on energy consumption.

Similarly to electric van models, the statistical methods corresponding to diesel van outperform both COPERT and CMEM-CONST. Both CMEM-1STAT and CMEM-2STAT give a similar performance, nonetheless the differences are larger than for CPEM-1STAT and CPEM-2STAT due to mass independent term partially consisting of a constant idle consumption. It should be noted that despite being applied to the full velocity profile, CMEM gives larger error than CMEM-1STAT and CMEM-2STAT. Since CMEM was used to estimate the required correction, corresponding value should provide an estimate of the lower error bound that can be achieved with the proposed methodologies. Nonetheless, the approaches outlined here are inherently probabilistic hence it is likely that for some of the data-points the estimate will have a high accuracy. When the number of samples goes to infinity the error of CMEM will be smaller than both CMEM-1STAT and CMEM-2STAT.

It is notable that COPERT results in a significantly worse performance than methodologies based on CMEM. One of the disadvantages of COPERT is an inability to specify precisely mass of the analysed vehicle. The range of masses in COPERT's vehicle sizes are broad, for example, N1-III weight class covers vehicles with a mass ranging between 1760-3500 kg. Since mechanical power is linear with respect to vehicle's mass this can result with errors up to 50%. Although COPERT is applicable in situations where emissions and energy consumption are estimated throughout whole networks, physics-based models should be used instead, if the performance of an individual vehicle is of interest.

In the future, the methodologies will be extended by incorporating additional information about the trip, such as road gradient along a route or estimated travel time, and about the analysed vehicle such as more detailed model of the engine or vehicle's efficiencies. Additionally, the use of different training sets will be explored with speed profiles that more closely resemble regional driving styles. Similarly, if datasets that contain energy consumption in logistics services were available, the statistical coefficients can be estimated using energy usage directly instead of approximations through CMEM and CPEM.

Acknowledgements

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